TEXTURE ANALYSIS AS A TOOL FOR MEDICAL DECISION SUPPORT. PART 1: RECENT APPLICATIONS FOR CANCER EARLY DETECTION

Dorota Duda

Faculty of Computer Science, Bialystok University of Technology, Białystok, Poland

Abstract: A great number of works have been devoted to developing different medical decision support systems, based on an image data. Such systems combine a wide range of methods for digital image analysis and interpretation. It has been proven that one of the most useful sources of information encoded in the image is its texture. Texture Analysis (TA) provides many important discriminating characteristics, not normally perceptible with visual inspection. With properly chosen TA methods, an image-based diagnosis could be considerably improved. However, the choice of the methods is not an easy task and often depends on the nuances of each diagnostic problem.
The present work provides an overview of the most frequently used methods for texture analysis (statistical, model-based, and filter-based) and shows their advantages and limitations. It also includes an overview of texture-based medical decision support systems, recently proposed for cancer detection and classification.

Keywords: medical imaging, image analysis, texture characterization, feature selection, computer aided diagnosis, CAD, medical decision support

A list of abbreviations is given at the end of this article.

1. Introduction

Different imaging modalities are presently available to assist clinicians in the detection and the diagnosis of human pathologies. Among them are: Computed Tomography (CT), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Magnetic Resonance Imaging (MRI), Ultrasonography (US), or Optical Imaging. With a constant improvement of image acquisition devices, the

Advances in Computer Science Research, vol. 11, pp. 61-84, 2014.

amount of diagnostic information obtained within a single study has considerably increased. In such a situation, the interpretation of image content based only on its visual inspection goes far beyond the human abilities. Indeed, an unarmed human eye can distinguish barely 100 gray levels, whereas the gray-scale images obtained nowadays (still commonly used) can encode many thousands of gray levels.

Since an experienced physician is not able to read all the useful image data without any additional equipment, a great deal of work has been devoted to develop different methods for (semi)automatic medical image analysis, interpretation, and recognition. As a result, many Computer-Aided Diagnosis (CAD) systems have been proposed over the past two decades. These systems combine a broad range of image analysis methods (including image segmentation and tissue characterization techniques), feature selection, and classification algorithms. The literature describes many examples of image-based CAD systems that have already found their application in various problems, concerning different organs and/or different imaging modalities. Among them, we can enumerate the systems for hepatic diseases recognition, based on the CT images (they will be detailed in the second part of the work [1]), on the MR images [2], or on the contrast-enhanced ultrasonography [3]. Another example concerns the breast lesion classification based on the ultrasound images [4–6] or on the Dynamic Contrast Enhanced (DCE) MR images [7–13]. The recognition of the prostate cancers on the basis of the DCE-MR images were also studied [14–22]. An exhaustive overview of the CAD systems for lung cancer recognition, based on the CT and/or the PET images can be found in [23]. Finally, the usefulness of CAD systems for brain tumor detection and classification from MRI were investigated in [24–30].

The advantage of CAD systems is that they improve considerably the image-based diagnosis, which reduces the necessity of using other methods, such as a fine needle aspiration biopsy or a surgical biopsy. Moreover, medical imaging is becoming continuously cheaper, faster, and less wasteful. Finally, it is certainly much less invasive (or even non-invasive) in comparison with many gold standard procedures.

The choice of the most appropriate methods for (semi)automatic image analysis and interpretation is not a trivial task. The works presented so far have shown that each diagnostic problem requires practically a re-validation of methods previously tested in similar domains. However, a good selection of such methods is crucial to guarantee the satisfactory tissue recognition. In 1979, Haralick stated that one of the most important sources of analyzed image region could be its texture [31]. It characterizes the spatial relationships between gray levels describing pixels within a considered image region (so called "Region of Interest", commonly abbreviated as ROI). Since then, numerous review studies have shown that texture analysis could

be highly useful in various problems related to the recognition of medical (and also nonmedical) images [32–38], as it provides a crucial information in terms of tissue discrimination. Moreover, many works have revealed that digital image analysis enables to detect the high order texture properties not accessible to visual inspection (see, for example, [31, 39–41]).

The aim of present work is to review the most frequently used methods for extraction of textural features. Three main TA approaches are considered: statistical, model-based, and filter-based. The remaining sections are organized as follows. In the next section, different methods of texture analysis are presented. Section 3 presents some recent results of their application in several diagnostic domains. Finally, in the last section, the main conclusions are drawn.

2. Overview of texture analysis methods

2.1 Gray Level Histogram

Features derived from a Gray Level Histogram (GLH) are based solely on the distribution of pixel gray levels and do not consider the relationships between neighboring pixels. They provide knowledge on the most and the less often occurring gray levels, on the concentration of the gray levels around their average, or on the degree of asymmetry in their distribution. On the contrary, they do not contain any information neither about the possible direction of the texture, nor about its structure. Nevertheless they are often used because of their invariability to translation or rotation, simplicity, and low memory and time requirements for their calculation. The most popular first-order features are:

- *range of gray levels*,
- *mean of gray levels* (measure of image brightness),
- *median gray level* (the second quartile),
- *gray level energy* (indicates how the gray levels are distributed),
- *variance of gray levels* (characterizes the distribution of gray levels around the mean),
- *gray level skewness* (measures the asymmetry of the gray-level histogram),
- *gray level kurtosis* (indicates the relative flattening of the gray-level histogram),
- *coefficient of variation* (the ratio of the standard deviation to the mean).

2.2 Co-Occurrence Matrices

Co-Occurrence Matrices (COM) were introduced by Haralick et al. [42]. This method consists in analyzing all the possible pairs of pixels, spaced apart by a fixed distance,

d, and arranged in a given direction, θ. Four pixel alignment directions (0°, 45°, 90°, and 135°), and different distances between the pixels in pairs can be considered. Typically, d takes small values. A combination (d,θ) determines thus unequivocally the relative position of pixels composing the pairs to analyze. A co-occurrence matrix $C(d,\theta)$ is of size $G \times G$, where G is the number of gray levels possible to be encoded in an image. Each element of co-occurrence matrix, c_{ij} $(i, j = 0, ..., G-1)$, represents a probability of occurrence of a pair of pixels with gray levels of i and j, for the first and for the second pixel, respectively. Several texture characteristics can be obtained on the basis of a co-occurrence matrix [42]:

- *energy* or *angular second moment* (measure of homogeneity of gray levels characterizing the pixels within an analyzed ROI),
- *contrast* or *inertia* (measure of contrast or local variations in pixel gray levels),
- *inverse difference moment* (measure of local homogeneity),
- *entropy* (quantifies a degree of randomness of the pixel gray levels),
- *correlation* (measures linear dependency of gray levels on neighboring pixels).

Other features can be calculated from the sums of probabilities that relate to specified intensity sums or differences [34]. In practice, this requires the construction of vectors whose components are the co-occurrence probabilities of pairs of pixels with a determined sum or difference of the gray levels. All possible sum / difference values are taken into account. The probabilities form a vector and are sorted in increasing order of corresponding sum or difference values. Some features derived from such vectors are:

- *sum average*,
- *sum variance*,
- *sum entropy*,
- *difference average*,
- *difference variance*,
- *difference entropy*.

Conners et al. [43] proposed two additional COM-based features, that measure the skewness (the lack of symmetry) of the matrix $C(d,\theta)$:

- *cluster shade*,
- *cluster prominence*.

For non-directed textures, several values of the same feature, corresponding to different arrangement directions, θ, but obtained for the same distance between pixels in pairs, can be averaged. Often feature values corresponding to different distances, d, are also averaged.

2.3 Run Length Matrix

Run Length Matrix (RLM) features are based on probabilities of pixel runs of each possible length, arranged in a certain direction [44]. Like in previous method, four standard directions of pixel runs are considered, $\theta = 0^\circ$, 45°, 90°, or 135°. A run-length matrix, $R(\theta)$, has G columns and M rows, where G is the number of image gray levels, and M is the maximum length of pixel run which can exist in an analyzed image region. The element r_{mg} ($m = 1,...,M$, and $g = 0,...,G$) of a run length matrix $R(\theta)$ is the number of existing pixel runs of a gray level g, having a length of m, and oriented in a direction θ.

Galloway initially proposed the following features, derived form a run length matrix.

- *short run emphasis*,
- *long run emphasis*,
- *gray level non-uniformity (distribution)*,
- *run length non-uniformity (distribution)*,
- *fraction of image in runs*.

The proposition of two additional features can be found in [45]:

- *low gray level runs emphasis*,
- *high gray level runs emphasis*.

Yet another work [46] proposes to use a *run length entropy* as a texture feature.

Also in this method, the values of the same feature corresponding to different directions of pixel runs can be averaged.

2.4 Gray Level Difference Matrices

Gray Level Difference Matrices (GLDM) are constructed with consideration of only the absolute values of differences between the gray levels of pixels, still considered in pairs [47]. Similarly to a COM-based method, also here four pixel alignment directions θ, and different distances, d, between the pixels in pairs can be considered. Further, all possible absolute differences in gray levels that can be encoded in the image are taken into account. For each absolute difference, the probability of finding a pair of pixels with just such a difference in the gray levels is calculated. The probabilities sorted in increasing order of corresponding absolute gray level differences form a vector $l(d,\theta) = [l_0, l_1, ..., l_{G-1}]^T$, where G is the number of gray levels possible to be encoded in an image.

Five textural features can be derived from the $l(d,\theta)$ vector:

- *mean* (measures a level of texture diversity),
- *energy* or *angular second moment* (measure of homogeneity of gray levels),
- *contrast* or *inertia* (measure of intensity contrast between a pixel and its neighbors),
- *inverse difference moment* (measure of the local homogeneity),
- *entropy* (quantifies a degree of randomness of the pixel gray levels).

All above features could be averaged when they are calculated for different θ and/or d parameters.

2.5 Gradient Matrices

Gradient-based features were introduced by Lerski et al. [48]. A gray-level gradient at a particular image point is a function of the differences between the gray levels of its neighboring pixels, aligned on vertical and horizontal lines passing through the point. Often a neighborhood of 3×3 pixels or 5×5 pixels is considered. The Gradient Matrix (GM) contains the values of the absolute gradient at each point of an analyzed image region, excluding its boundaries.

Features derived from a gradient matrix are the following:

- *mean*,
- *variance*,
- *skewness*,
- *kurtosis*,
- percentage of pixels with nonzero gradient.

They can provide the information on the uniformity, homogeneity, or the roughness of the texture. They may also indicate the presence or absence of edges.

2.6 Texture Feature Coding Method

Texture Feature Coding Method (TFCM) was proposed by Horng et al. [49]. The method consists of three steps. First, an image is transformed. The transformation consists of assigning to each pixel (except for the pixels located at the edges of a considered ROI) a value that measures a degree of heterogeneity (of variation, of diversity) of the local gray levels of its neighbors. The authors call this measure a "Texture Feature Number" (TFN). Only a neighborhood of 3×3 pixels is considered. Afterwards, a histogram of Texture Feature Numbers, and co-occurrence matrices are constructed, based on a transformed image. Finally, several texture descriptors are obtained, either from a TFN histogram:

– *coarseness*,
– *homogeneity*,
– *mean convergence* (indicates how close the texture approximates the mean),
– *variance* (measures deviation of TFNs from the mean),

either from a TFN-based co-occurrence matrix:

– *entropy*,
– *code similarity* (assesses the density of the same TFNs in a 3×3 neighborhood),
– *resolution similarity* (measures the local homogeneity of TFNs).

2.7 Autocorrelation Coefficients

Autocorrelation Coefficients (AC) [50] expresses the correlation of the gray levels describing pixels within a defined neighborhood. It is the function of the vertical (Δx) and the horizontal (Δy) distance between the considered pixels in pairs. Usually such distances are relatively small. In order to normalize the autocorrelation coefficients a gray level of each pixel is decreased by the mean gray level. Normalized autocorrelation coefficients are independent of the image brightness, and can be regarded as textural features. They can provide knowledge on the spatial relationship between the texture patterns, and the average size of texture patterns.

2.8 Fractal Model (FM)

Fractal Model (FM) was described in several works [51–53]. Unfortunately, each of them gives different definitions of a fractal object. Mandelbrot characterized fractals as self-similar objects, whose parts are similar to the whole, and whose topological dimension is not an integer [51]. The fractal dimension of an object reflects the extent to which this object fills the space or the rate of its diversity, the degree of irregularity of the object.

A gray-level image can be considered as a topographic surface in three-dimensional space, where two dimensions are those of the image plane and the third one (height) is the gray level of image pixels. The fractal dimension of such a surface can be used as a texture descriptor. It can measure the irregularity and the roughness of the texture. Irregular surfaces (corresponding to a diversified textures) have relatively high fractal dimension, while the smooth ones are characterized by the low fractal dimension.

So far, several methods for calculating a fractal dimension of a texture have been reported in the literature. Among them we can mention: the approaches based on the fractional Brownian motion model [54, 55], the box-counting methods [56, 57], the mass-radius methods [58], the wavelet-based methods [59], and others [60–63].

2.9 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) of an image consists in its convolution with two filters, the low-pass and the high-pass one, separately throughout the image rows and separately throughout the image columns. The Mallat algorithm for DWT [64] divides the image into the four sub-images, each of which is linearly two times smaller than the decomposed image. Each sub-image can then be divided in the same manner. Thus multiple resolution levels are obtained. Four sub-band images created at each decomposition step are denoted: d^{LL}, d^{LH}, d^{HL}, and d^{HH}. They are created by applying, respectively: the low-pass filter for rows and columns (LL), the low-pass filter for rows and the high-pass filter for columns (LH), the high-pass filter for rows and the low-pass filter for columns (HL), the low-pass filter for rows and columns (LL). The component d^{LL} is created by calculating the average of disjoint groups of 2×2 pixels, using Haar transform. It is therefore an approximation (simplified representation) of the transformed image. Further sub-bands represent the vertical (LH), the horizontal (HL) and the diagonal (HH) image information. On the basis of them an edge energy at three directions can be calculated. It is also possible to analyze the energy distribution in each sub-band image. The image d^{LL} is used only for DWT calculation at the next scale.

2.10 Laws' Texture Energy measures

Laws' Texture Energy (LTE) measures [65] are useful for estimating the frequency of the image elements, such as ripples, edges, or spots. Laws proposed to transform the images using linear filters. During the transformation, each image pixel is assigned a value that is a combination of initial gray levels of pixels belonging to a neighborhood of a transformed pixel. Usually two types of neighborhood are considered: 3×3 pixels and 5×5 pixels. The weights of the neighboring pixels are defined by a zero-sum convolution matrix (so-called Laws' mask). For each pair of asymmetric masks, the resulting images could be added. In this case, images obtained with an application of symmetric masks are multiplied by two. On the basis of a transformed image, the entropy can be calculated. Also, the filtered images can be once again subjected to further transformation, that results in creation of texture energy images. Finally, the features such as: *mean*, *variance*, *skewness*, and *kurtosis* can be calculated from the resulting images.

3. Recent applications for cancer early detection

The following describes the most recently published works, considering textural features as useful tissue descriptors. Each of the systems aims at cancer detection and

characterization from MRI images. Three main diagnostic problems are considered: prostate cancer diagnosis, brain tumor diagnosis, and breast lesion classification.

3.1 Prostate cancer diagnosis

The (semi)automated CAD systems using a texture analysis as a prostatic tissue descriptor are still not broadly developed. Most of the existing works are based mainly on the pharmacokinetic models, employing the signal-to-time curves, in order to find perfusion parameters (e.g. [18]). Such models give an information about the propagation of contrast product, extracted from the T1-weighted DCE MRI sequences. Other systems exploit also diffusion weighted image features (e.g. [66]), not based on textural properties. However some works exploiting the potential of TA in prostatic tissue differentiation have appeared in recent few years [17, 19–22, 66, 67].

Lopes et al. [17] employed fractal and multifractal textural features to characterize prostatic tissues on T2-weighted MR images. Their system was able to recognize two types of tissue: a tumorous and a non-tumorous one. The fractal dimension was computed using the variance method. The multifractal spectrum was estimated by a modified multifractional Brownian motion model. The classification was performed with Support Vector Machines (SVM) [68] and an adaptive boosting voting scheme (AdaBoost) [69]. The best result was obtained by AdaBoost classifier: 85% and 93%, for sensitivity and specificity, respectively. Moreover, the results obtained by the proposed system were better than those corresponding to the application of classical textural features, derived from co-occurrence matrices, wavelets, or Gabor filters [70]. The fractal method turned also to be most robust against signal intensity variations.

Niaf et al. [19] analyzed simultaneously different MRI sequences (T1-, T2-, and diffusion-weighted) in order to differentiate between: (i) malignant vs benign prostatic tissues, and (ii) malignant vs nonmalignant, but suspicious ones. The CAD system proposed in their work combined functional parameters, extracted from DCE images, together with textural features derived from the three considered MRI sequences. First-order and second-order (COM-based) textural features were utilized. Four classifiers were applied: nonlinear SVM, Linear Discriminant Analysis (LDA) [71], k-Nearest Neighbors (k-NN) [72] and Bayesian one [72]. The system performances were assessed by the areas under the Receiver Operating Characteristic (ROC) Curves (AUC) [73]. The best result was achieved with the SVM classifier and was 0.89 and 0.82, for the first (i) and for the second (ii) discrimination problem, respectively.

Peng et al. [66] assessed the utility of T2-weighted MRI texture features and diffusion weighted image features in distinguishing prostate cancer from normal tissue.

Here, the LDA and the areas under the ROC curves were used to evaluate the performance of each feature. Among many tested texture characteristics, the *sum average* turned to be the best feature. Nevertheless it did not outperform some of the *Apparent Diffusion Coefficient* (ADC) features, that measure the magnitude of diffusion (of water molecules) within a tissue. The combination of three features (*sum average* and two ADCs) yielded AUC values of 0.94 and 0.89 on the images acquired with the Phillips and the GE scanner, respectively.

Duda et al. [20] proposed to analyze simultaneously triplets of prostate MR images, corresponding to the same prostate slice, but derived from different image series: the contrast-enhanced T1-, the T2-, and the diffusion-weighted one. Two classes of prostatic tissue were differentiated: tumorous and healthy. Six different texture analysis methods were used: GLH-, COM-, RLM-, GM-, AC-, and FM-based. Their ability of characterizing prostatic tissue was assessed with three classifiers: Logistic Regression (LR) [74], Neural Network (NN) [75, 76] and SVM. The 10-fold cross-validation [71] was used to assess the classification accuracies. The best overall classification result exceeded 99% and corresponded to the application of the SVM classifier.

Ginsburg et al. [67] tried to predict the probability of developing biochemical recurrence risk (associated with raised risk of metastases and prostate cancer-related mortality) following the radiation therapy. In their work they evaluated the efficiency of different textural features, extracted from the T2-weighted images. They considered: first-order statistical features, gradients (involving image convolutions with Sobel and Kirsch operators [77]), co-occurrence matrices-based, and Gabor wavelet features [78]. For each feature, its prognostic potential and its contribution to classification results was assessed. As a classifier, a Logistic Regression was used. Despite of poor resolution of images, available for the experiments, the area under the ROC curve for the best three features (the Gabor wavelet ones) reached 0.83.

Litjens et al. [21] developed a fully automated computer-aided detection system, which was able to differentiate between patients with and without prostate cancer. Their study based on: T2-weighted, proton density-weighted, dynamic contrast enhanced, and diffusion-weighted images. Thus several types of features could be used. They were: based on signal intensity, representing pharmacokinetic behavior, anatomical features, blobness, and finally – texture descriptors, based on Gaussian texture models. These latter characteristics contributed to the ability of the system to achieve a performance comparable to the one achieved by radiologists.

Finally, Molina et al. [22] proposed a system that combined different features (anatomic, textural, and functional) in order to recognize three classes of prostatic tissue: cancerous, unhealthy non-cancerous, and healthy. Three different series of

MR images were considered in the work: T2-weighted, Dynamic-Contrast Enhanced Plasma Flow (DCE-PF) and DCE Mean Transit Time (DCE-MTT). Nevertheless, the texture information was extracted from only the structural T2-weighted images. In the work, three groups of features were used: the first-order statistical descriptors, and the second-order ones, derived from: a Neighboring Gray Level Dependence Matrix (NGLDM) [79] and a Neighborhood Gray-Tone Difference Matrix (NGTDM) [80]. Experiments showed that the use of texture descriptors could provide more relevant discriminative information than the considered functional parameters. The average sensitivity and specificity obtained with the system was of 84.46% and 78.06%, respectively.

3.2 Brain tumor diagnosis

A few algorithms have been recently developed for brain tumor detection and classification, based on MR images of different modalities.

In 2012, John [25] proposed a system for brain tumor classification from T2-weighted MR images. The system was able to recognize the three tissue types: normal, non-cancerous (benign) brain tumor and cancerous (malignant) brain tumor. The tissue characterization process consisted of two stages. First, the images were decomposed with the wavelet transform. Next – the co-occurrence matrix-based textural features were extracted from the LH and HL sub-bands of the first five levels of wavelet decomposition. Five textural features were considered: *energy*, *contrast*, *correlation*, *homogeneity* and *entropy*. Finally, they were fed into a Probabilistic Neural Network (PNN) [81] for further classification and tumor detection. The system achieved the classification accuracy of near 100%.

Patil et al. [26] tried to differentiate the four grades of Astrocytoma (from Grade I to Grade IV). Their approach consisted of several stages: image preprocessing, segmentation, feature extraction and classification. Feature extraction involved using the co-occurrence techniques, providing a set of 11 features. Finally, a Probabilistic Neural Network has been developed to differentiate between different grades of considered brain tumor. The overall accuracy of the system (obtained on the test set) was of 94.87%.

The system presented by Islam et al. [27] was designed for the detection and the segmentation of brain tumors from non-enhanced T1-weighted, T2-weighted, and FLAIR images. Two different tumor groups were considered in their study: astrocytoma and medulloblastoma. The tissue was characterized here using fractal and multifractal (based on fractional Brownian motion model) methods. The features corresponding to different modalities were fused. As a classifier, an extension of AdaBoost

algorithm was used. The system was tested on 14 patients with over 300 images and showed its high efficacy.

Jayachandran et al. [28] evaluated a system for detection and classification of brain tumors on T1-weighted post contrast (gadolinium-based) images. Their system was able to find tissue characteristics, to reduce the feature space, and to classify tissues into two categories: tumorous and non-tumorous one. Texture analysis was performed with the co-occurrence matrices. The Principal Component Analysis (PCA) [82] was used in order to reduce the feature space. Finally – the Fuzzy based Support Vector Machine was applied for a classification. Experiments were conducted on 80 brain MRI images. The proposed methodology resulted in quite high rates of correctly classified cases (more than 95%).

Sachdeva et al. [29] developed a system aimed at the differentiation of six tissue classes. They corresponded to the primary brain tumors: astrocytoma, multiform glioblastoma, childhood tumor – medulloblastoma, meningioma, secondary tumor – metastatic, and normal regions. Their analyses involved using post-contrast T1-weighted MR images. First, tumors were segmented with the content-based active contour model [83]. Then over two hundred intensity and texture features were used as tissue characteristics. Texture analysis considered: Laplacian of Gaussian (LoG) filters [77], co-occurrence matrices, rotation invariant Local Binary Patterns (LBP) [84], directional Gabor texture features [85], gray-level histogram, and rotation invariant circular Gabor features [86]. Due to the large number of candidate features, a feature space was reduced with the PCA. Then, an artificial Neural Network was applied in order to perform the classification. The robustness of the proposed system was tested using quite a large database (856 ROIs), with a partitioning of data into a training and a test set. The overall classification accuracy was of 85.23%.

Most recently, Tiwari et al. [87] assessed different groups of textural features, in terms of their ability to differentiate radiation necrosis (a radiation induced treatment effect) from recurrent brain tumors. In fact this task is very difficult to the human observer, because both pathological processes results in almost the same morphological appearance on standard MRI. So far, the diagnosis was possible only through a surgical intervention. The aim of the study was thus to find a set of features that could accentuate subtle differences between both pathologies, and – further – to determine which MRI protocol could provide the most discriminating information. Three MR image series were considered: T1-weighted, T2-weighted and FLAIR. The examined textural features were derived from: co-occurrence matrices, neighboring gray-level dependence matrices, Laplacian pyramids [88], Laws' texture energy measures, and Histogram of Gradient orientations (HoG) [89]. In total, 119 features were assessed. Each feature was assessed by Principal Component Analysis-based Variable

Importance Projection (PCA-VIP), developed by authors. Then a random-forest classifier [90] was used to differentiate between considered pathologies. The experiments showed that HoG, COM, and Laws' features were the most suitable ones for the problem solution. The best MRI image series turned out to be the contrast-enhanced T1-weighted one.

3.3 Breast lesion classification

The breast lesion characterization and differentiation from MRI images involves often a simultaneous analysis of images derived from different series, like T1-weighted (non-enhanced or contrast-enhanced), T2-weighted, diffusion-weighted, or others. In this case it is important not only to find potentially reliable pathology-related features, but also to combine properly the tissue descriptors corresponding to different image series. Here, textural features are often combined with other lesion descriptors: morphological, intensity kinetic features (based on signal-to-time curve), or shape descriptors.

Bhooshan et al. [8] combined textural features from both DCE T1- and T2-weighted MR images in order to recognize benign and malignant breast lesions. For the T1-weighted sequences, only the first post-contrast image was used for texture analysis. As texture descriptors, again the COM-based features were used. The contrast product propagation was characterized by typical kinetic parameters obtained from signal-to-time curves. The system was able to perform an automatic lesion segmentation, then – the features were automatically extracted. In the experimental stage, a stepwise feature selection was performed by Linear Discriminant Analysis. The selected features were merged by with Bayesian artificial Neural Network classifier. The leave-one-out cross-validation [71], and the areas under the ROC curve were used to assess the performance of tested sets of features. The experiments showed, that the combination of texture characteristics, obtained from both T1-, and T2-weighted images may outperform the conventional analysis of T1-weighted contrast-enhanced sequences. When all the features were considered, the best result was achieved. It gave the area under the ROC curve of 0.85.

Agner et al. [12] also tried to distinguish malignant from benign lesions. In their work, they compared several approaches to lesion characterization, giving different types of tissue descriptors: morphological features, signal intensity kinetic features, and textural features. The latter ones were based on gray-level histogram, gradients, and co-occurrence matrices. The study introduced a notion of "textural kinetics", that characterized texture evolution under contrast product propagation in DCE MRI. At first, textural features were calculated at each moment of contrast product propaga-

tion, and the "textural kinetics curve" was created basing on the set of feature values. Afterwards, a third order polynomial was fitted to such curve in order to characterize its shape. Four polynomial coefficients constituted the feature vector. Feature vectors were classified with the SVM and the AdaBoost classifiers. Experiments on 41 cases, showed that textural kinetics features outperformed the other ones (morphological, descriptors of signal intensity kinetics, and these based on "static" textures). The best classification accuracy was about 90%.

Nagarajan et al. [13] used a multi-image texture analysis for breast lesion classification. In order to differentiate two types of small lesions (benign and malignant) they analyzed simultaneously five post-contrast T1-weighted images. A multi-image texture was characterized by five values of the same textural feature. Each value corresponded to a different moment of contrast agent propagation. Only the COM-based textural features were considered. The tissue recognition was performed with Support Vector Regression and a fuzzy k-Nearest Neighbor classifier. The classifier performances were determined through the ROC analysis. The highest AUC value observed was of 0.82. Experiments also showed that textural features extracted from the third and fourth post-contrast image contributed the most to the correct tissue differentiation.

Recently, Cai et al. [10] combined dynamic contrast-enhanced and diffusion-weighted images (DWI), also to recognize benign lesions and malignant ones. The lesion regions were obtained with a semi-automated segmentation method. Then, four types of tissue descriptors were considered: kinetic, morphological, textural (co-occurrence matrix-based), and DWI features. In order to select the most robust features, a hybrid filter-wrapper algorithm [91] was applied. Finally, various classifiers (SVM, Bayesian, k-NN, LR) were used to evaluate the diagnostic performance of the selected features. The study comprised of 234 female patients. The classification accuracy was assessed with a 10-fold cross-validation and ROC characteristics. Finally, seven selected features (among them – three textural features) were found to be statistically different between the malignant and the benign groups, and their combination gave the highest classification accuracy – 93%.

Still in 2014, Pang et al. [11] presented a fully automated CAD system for the classification of malignant and benign masses. The system included a breast segmentation method, the mass segmentation method (described in [92]), feature extraction stage, feature selection (with the ReliefF [93] algorithm), and the SVM classifier. As tissue descriptors, morphological and textural features were used. Like in previous study, the texture analysis was performed using a co-occurrence matrix-based approach. A database comprised 120 cases. For the leave-one-out classifier assessment method, the accuracy was of 90.0%.

4. Conclusion

The present study enumerated the most commonly used methods for texture analysis. In addition to a brief description of the methods, it also included a short interpretation of the meaning of the parameters derived from each method. An overview of recently proposed works, considering textural features as reliable tissue descriptors in different classification problems, showed that the list of TA methods, presented in Section 2, is not exhaustive. The variety of methods proposed in the literature is far much larger. Experiments show, that each diagnostic problem, each image modality, may require the use of newer and newer procedures guaranteeing satisfactory classification results. Nevertheless, it could be noticed, that some groups of textural features show their huge potential more often than others. Among them the most powerful ones are the statistical features, obtained from the co-occurrence matrices. Such features were considered in almost all the quoted systems. The first-order statistics are less popular, however they are also tested because of their simplicity. Quite often a fractal model is used to find reliable texture characteristics. Also good are methods involving an image filtering.

To sum up the first part of the work, it can be concluded, that texture analysis has repeatedly demonstrated its valuable potential in the cancer early detection and differentiation. The implementation of many referred systems might certainly improve the image-based diagnosis, reducing the need for invasive procedures. The further development of imaging techniques, and the continuous work to improve the digital image-analysis methods may result in physicians more frequently refraining from the use of any invasive procedure.

Abbreviations

AdaBoost: Adaptive Boosting algorithm
ADC: Apparent Diffusion Coefficient
AUC: Area Under the ROC Curve
CAD: Computer-Aided Diagnosis
COM: Co-Occurrence Matrix
CT: Computed Tomography
DCE: Dynamic Contrast Enhanced (in MRI)
DCE-MTT: DCE Mean Transit Time (in MRI)
DCE-PF: DCE Plasma Flow (in MRI)
DWI: Diffusion-Weighted Imaging (in MRI)

DWT: Discrete Wavelet Transform
FLAIR: Fluid-Attenuated Inversion Recovery (in MRI)
FM: Fractal Model
GLDM: Gray Level Difference Matrix
GLH: Gray Level Histogram
GM: Gradient Matrix
HoG: Histogram of Gradient orientations
k-NN: *k*-Nearest Neighbors (classifier)
LBP: Local Binary Pattern
LoG: Laplacian of Gaussian
LR : Logistic Regression (classifier)
LTE: Laws' Texture Energy
MR: Magnetic Resonance
MRI: Magnetic Resonance Imaging
AC: Autocorrelation Coefficient
NGLDM: Neighboring Gray Level Dependence Matrix
NGTDM: Neighborhood Gray-Tone Difference Matrix
NN: Neural Network (classifier)
PCA: Principal Component Analysis
PCA-VIP: PCA-based Variable Importance Projection
PET: Positron Emission Tomography
PNN: Probabilistic Neural Network (classifier)
RLM: Run Length Matrix
ROC: Receiver Operating Characteristic
ROI: Region of Interest
SPECT: Single Photon Emission Computed Tomography
SVM: Support Vector Machines (classifier)
T1: longitudinal (or spin-lattice) relaxation time (in MRI)
T2: transverse (or spin-spin) relaxation time (in MRI)
TA: Texture Analysis
TFCM: Texture Feature Coding Method
TFN: Texture Feature Number
US: Ultrasonography

References

[1] Duda, D.: Texture analysis as a tool for medical decision support. Part 2: Classification of liver disorders based on Computed Tomography images, Advances in Computer Science Research 11, 2014, pp. 85-108.

[2] Zhang, X., Kanematsu, M., Fujita, H., Zhou, X., Hara, T., Yokoyama, R., Hoshi, H.: Application of an artificial neural network to the computer-aided differentiation of focal liver disease in MR imaging, Radiol. Phys. Technol. 2(2), 2009, pp. 175-182.

[3] Shiraishi, J., Sugimoto, K., Moriyasu, F., Kamiyama, N., Doi, K.: Computer-aided diagnosis for the classification of focal liver lesions by use of contrast-enhanced ultrasonography, Medical Phys. 35(5), 2008, pp. 1734-1746.

[4] Chabi, M.L., Borget, I., Ardiles, R, Aboud, G., Boussouar, S., Vilar, V., Dromain, C., Balleyguier, C.: Evaluation of the accuracy of a computer-aided diagnosis (CAD) system in breast ultrasound according to the radiologist's experience, Acad. Radiol. 19(3), 2012, pp. 311-319.

[5] Tan, T., Platel, B., Huisman, H., Sanchez, C.I., Mus, R., Karssemeijer, N.: Computer-aided lesion diagnosis in automated 3-D breast ultrasound using coronal spiculation, IEEE Trans. Med. Imag. 31(5), 2012, pp. 1034-1042.

[6] Wang, Y., Wang, H., Guo, Y., Ning, C., Liu B., Cheng, H.D., Tian, J.: Novel computer-aided diagnosis algorithms on ultrasound image: effects on solid breast masses discrimination, J. Digit. Imaging 23(5), 2012, pp. 581-591.

[7] Agliozzo, S., De Luca, M., Bracco, C., Vignati, A., Giannini, V., Martincich, L., Carbonaro, L.A., Bert, A., Sardanelli, F., Regge, D.: Computer-aided diagnosis for dynamic contrast-enhanced breast MRI of mass-like lesions using a multiparametric model combining a selection of morphological, kinetic, and spatiotemporal features, Med. Phys. 39(4), 2012, pp. 1704-1715.

[8] Bhooshan, N., Giger, M., Lan, L., Li, H., Marquez, A., Shimauchi, A., Newstead, G.M.: Combined use of T2-weighted MRI and T1-weighted dynamic contrast-enhanced MRI in the automated analysis of breast lesions, Magn. Reson. Med. 66(2), 2011, pp. 555-564.

[9] Rakoczy, M., McGaughey, D., Korenberg, M.J., Levman, J., Martel, A.L.: Feature selection in computer-aided breast cancer diagnosis via dynamic contrast-enhanced magnetic resonance images, J. Digit. Imaging 26(2), 2013, pp. 198-208.

[10] Cai, H., Peng, Y., Ou, C., Chen, M., Li, L.: Diagnosis of breast masses from dynamic contrast-enhanced and diffusion-weighted MR: A machine learning approach, PLOS ONE 9(1), 2014, e87387, pp. 1-7.

[11] Pang, Z., Zhu, D., Chen, D., Li, L., Shao, Y.: A computer-aided diagnosis system for dynamic contrast-enhanced MR images based on level set segmentation and ReliefF feature selection, Computational and Mathematical Methods in Medicine, Article ID 450531, 2014, pp. 1-10.

[12] Agner, S.C., Soman, S., Libfeld, E., McDonald, M., Thomas, K., Englander, S., Rosen, M.A., Chin, D., Nosher, J., Madabhushi, A.: Textural kinetics: a novel dynamic contrast-enhanced (DCE)-MRI feature for breast lesion classification, J. Digit. Imaging. 24(3), 2011, pp. 446-463.

[13] Nagarajan, M.B., Huber, M.B., Schlossbauer, T., Leinsinger, G., Krol, A., Wismuller, A.: Classification ofsmall lesions in breast MRI: Evaluating the role of dynamically extracted texture features through feature selection, J. Med. Biol. Eng. 33(1), 2013, pp. 59-68.

[14] Puech, P., Betrouni, N., Makni, N., Dewalle, A.S., Villers, A., Lemaitre, L.: Computer-assisted diagnosis of prostate cancer using DCE-MRI data: design, implementation and preliminary results, Int. J. Comput. Assist. Radiol. Surg. 4(1), pp. 1-10, 2009.

[15] Firjany, A., Elnakib, A., El-Baz, A., Gimel'farb, G., El-Ghar, M.A., Elmagharby, A.: Novel Stochastic Framework for Accurate Segmentation of Prostate in Dynamic Contrast Enhanced MRI, In Madabhushi, A., Dowling, J., Yan, P., Fenster, A., Abolmaesumi, P., Hata, N. (Ed): Lect. Notes Comput. Sc. 6367, Springer-Verlag Berlin Heidelberg, 2010, pp. 121-130.

[16] Vos, P.C., Hambrock, T., Barenstz, J.O., Huisman, H.J.: Computer-assisted analysis of peripheral zone prostate lesions using T2-weighted and dynamic contrast enhanced T1-weighted MRI, Phys. Med. Biol. 55(6), 2010, pp. 1719-1734.

[17] Lopes, R., Ayache, A., Makni, N., Puech, P., Villers, A., Mordon, S., Betrouni, N.: Prostate cancer characterization on MR images using fractal features, Med. Phys. 38(1), 2011, pp. 83-95.

[18] Sung, Y.S., Kwon, H.J., Park, B.W., Cho, G., Lee, C.K., Cho, K.S., Kim, J.K.: Prostate cancer detection on dynamic contrast-enhanced MRI: computer-aided diagnosis versus single perfusion parameter maps, AJR Am. J. Roentgenol. 197(5), 2011, pp. 1122-1129.

[19] Niaf, E., Rouviere, O., Mege-Lechevallier, F., Bratan, F., Lartizien, C.: Computer-aided diagnosis of prostate cancer in the peripheral zone using multiparametric MRI, Phys. Med. Biol. 57(12), 2012, pp. 3833-3851.

[20] Duda, D., Kretowski, M., Mathieu, R., de Crevoisier, R., Bezy-Wendling, J.: Multi-image texture analysis in classification of prostatic tissues from MRI.

Preliminary results. In Pietka, E., Kawa, J., Wieclawek, W. (Ed): Adv. Intell. Soft. Comp. 283, Springer, Switzerland, 2014, pp. 139-150.

[21] Litjens, G., Debats, O., Barentsz, J., Karssemeijer, N., Henkjan H.: Computer-aided detection of prostate cancer in MRI, IEEE Trans. Med. Imag. 33(5), 2014, pp. 1083-1092.

[22] Molina, J.F.G., Zheng, L., Sertdemir, M.. Dinter, D.J., Schonberg, S., Radle, M.: Incremental Learning with SVM for Multimodal Classification of Prostatic Adenocarcinoma, PLoS ONE 9(4), e93600, 2014, pp. 1-14.

[23] El-Baz, A., Beache, G.M., Gimel'farb, G., Suzuki, K., Okada, K., Elnakib, A., Soliman, A., Abdollahi, B.: Computer-aided diagnosis systems for lung cancer: challenges and methodologies, Int. J. Biomed. Imaging 2013, 942353, 2013, pp. 1-46.

[24] Ambrosini, R.D., Wang, P., O'Dell, W.G.: Computer-aided detection of metastatic brain tumors using automated 3-D template matching, J. Magn. Reson. Imaging 31(1), 2010, pp. 85-93.

[25] John, P.: Brain tumor classification using wavelet and texture based neural network, Int. J. Sci. Eng. Research 3(10), 2012, pp. 1-7.

[26] Patil, S., Udupi, V.R.: A Computer Aided Diagnostic System for Classification of Brain Tumors Using Texture Features and Probabilistic Neural Network, Int. J. Comput. Sc. Eng. Inf. Technol. Research 3(1), 2013, pp. 61-66.

[27] Islam, A., Reza, S.M.S., Iftekharuddin, K.M.: Multifractal Texture Estimation for Detection and Segmentation of Brain Tumors, IEEE Trans. Biomed. Eng. 60(11), 2013, pp. 3204-3215.

[28] Jayachandran, A., Dhanasekaran, R.: Brain tumor detection and classification of MR images using texture features and fuzzy SVM classifier, Res. J. Appl. Sci. Eng. Technol. 6(12), 2013, pp.2264-2269.

[29] Sachdeva, J., Kumar, V., Khandelwal, N., Ahuja, C.K.: Segmentation, feature extraction, and multiclass brain tumor classification J. Digit. Imaging. 26(6), 2013, pp. 1141-1150.

[30] Selvanayaki, K., Karnan, M.: CAD System for Automatic Detection of Brain Tumor through Magnetic Resonance Image-A Review, Int. J. Eng. Sc. Technol. 2(10), 2010, pp. 5890-5901.

[31] Haralick, R.M.: Statistical and structural approaches to texture, Proc. of the IEEE 67(5), 1979, pp. 786-804.

[32] Castellano, G., Bonilha, l., Li, L.M., Cendes, F.: Texture analysis of medical images, Clin. Radiol. 59(12), 2004, pp. 1061-1069.

[33] Hajek, M., Dezortova, M., Materka, A., Lerski R.A. (Ed): Texture Analysis for Magnetic Resonance Imaging, Med4Publishing, Prague, Czech Republic, 2006.

[34] Bankman, I.N.: Handbook of Medical Image Processing and Analysis, Second Edition, Academic Press, 2008.

[35] Nielsen, B., Albregtsen, F., Danielsen, H.E.: Statistical nuclear texture analysis in cancer research: a review of methods and applications, Crit. Rev. Oncog. 14(2-3), 2008, pp. 89-164.

[36] Szczypinski, P.M., Strzelecki, M., Materka, A., Klepaczko, A.: MaZda – A software package for image texture analysis, Comput. Meth. Prog. Bio. 94(1), 2009, pp. 66-76.

[37] Nailon, W.H.: Texture analysis methods for medical image characterisation, In Mao, Y. (Ed): Biomedical Imaging, InTech, Open, 2010, pp. 75-100.

[38] Kassner, A., Thornhill, R.E.: Texture Analysis: A Review of Neurologic MR Imaging Applications, Am. J. Neuroradiol. 31, 2010, pp. 809-816.

[39] Tuceryan, M., Jain, A. K.: Texture analysis, In Chen, C.H., Pau, L.F., Wang, P.S.P. (Ed): The Handbook of Pattern Recognition and Computer Vision, World Scientific Publishing Co., Singapore, 2nd edition, 1998, pp. 207-248.

[40] Zhang, J., Tan, T.: Brief review of invariant texture analysis methods, Pattern Recognition 35(3), 2002, pp. 735-747.

[41] Xie, X.: A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques, Electron. Lett. Comp. Vision Image Anal. 7(3), 2008, pp. 1-22.

[42] Haralick, R. M., Shanmugam K., Dinstein I.: Textural features for image classification, IEEE Trans. Syst., Man, Cybern., Syst 3, 1973, pp. 610-621.

[43] Conners, R.W., Harlow, C.A.: Toward a structural textural analyzer based on statistical methods, Comput. Vision Graph. 12(3) 1980, pp. 224-256.

[44] Galloway, M.M.: Texture analysis using gray level run lengths, Comput. Vision Graph. 4(2), 1975, pp. 172-179.

[45] Chu, A., Sehgal, C.M., Greenleaf, J.F.: Use of gray value distribution of run lengths for texture analysis, Pattern Recognition Letters, 11(6), 1990, pp. 415-420.

[46] Albregtsen, F., Nielsen, B., Danielsen, H.E.: Adaptive gray level run length features from class distance matrices, Proc. 15th Int. Conf. on Pattern Recognition, 3, 2000, pp. 738-741.

[47] Weszka, J.S., Dyer, C.R., Rosenfeld, A.: A Comparative Study of Texture Measures for Terrain Classification, IEEE Trans. Systems, Man, Cybernetics, 6, 1976, pp. 269-285.

[48] Lerski, R.A., Straughan, K., Shad, L., Boyce, D., Bluml, S., Zuna, I.: MR Image Texture Analysis – An Approach to Tissue Characterization, Magn. Reson. Imaging 11(8), 1993, pp. 873-887.

[49] Horng, M.H., Sun, Y.N., Lin, X.Z.: Texture feature coding method for classification of liver sonography, Comput. Med. Imag. Grap 26(1), 2002, pp. 33-42.

[50] Gonzalez, R.C., Woods, R.E.: Digital Image Processing, Second edition, Reading, MA: Addison-Wesley, 2002.

[51] Mandelbrot, B.: The Fractal Geometry of Nature, block W. H. Freeman and Co., NY, 1982.

[52] Falconer, K.: Fractal Geometry, Mathematical Foundations and Applications, Second edition, Willey, 2003.

[53] Edgar, G.: Measure, Topology and Fractal Geometry, Second edition, Springer-Verlag, 2008.

[54] Chen, C., Daponte, J.S., Fox, M.D.: Fractal feature analysis and classification in medical imaging, IEEE Trans. Med. Imag. 8(2), 1989, pp. 133-142.

[55] Chen, E.L., Chung, P.C., Chen, C.L., Tsai, H.M., Chang, C.I.: An automatic diagnostic system for CT liver image classification, IEEE Trans. Biomed. Eng. 45(6), 1998, pp. 783-794.

[56] Li, J., Du, Q.: An improved box-counting method for image fractal dimension estimation, Pattern Recognition 42(11), 2009, pp. 2460-2469.

[57] Sankar, D., Thomas. T.: Fractal Features based on Differential Box Counting Method for the Categorization of Digital Mammograms, International Journal of Computer Information Systems and Industrial Management Applications 2, 2010, pp. 11-19.

[58] Landini, G., Rippin, J.W.: Notes on the implementation of the mass-radius method of fractal dimension estimation, Comput. Appl. Biosci. 9(5), 1993, pp. 547-550.

[59] Jones, C.L., Jelinek, H.F.: Wavelet packet fractal analysis of neuronal morphology, Methods 24(4), 2001, pp. 347-458.

[60] Pentland, A.P.: Fractal-Based Description of Natural Scenes, IEEE Trans. Pattern Anal. Mach. Intell. PAMI-6(6), 1984, pp. 661-674.

[61] Maragos, P., Sun, F.K.: Measuring the Fractal Dimension of Signals: Morphological Covers and Iterative Optimization, IEEE Trans. Signal Process. 41(1), 1993, pp. 108-121.

[62] Backes, A.R., Bruno, O.M.: A new approach to estimate fractal dimension of texture images, In Elmoataz, A., Lezoray, O., Nouboud, F., Mammass, D. (Ed): Lect. Notes Comput. Sc. 5099, Springer, 2008, pp. 136-143.

[63] Kilic, K.I., Abiyev, R.H.: Exploiting the synergy between fractal dimension and lacunarity for improved texture recognition, Signal Processing 91(10), 2011, pp. 2332-2344.

[64] Mallat, S.G.: A theory for multiresolution signal decomposition: The wavelet representation, IEEE Trans. Pattern Anal. Mach. Intell. 11(7), 1989, pp. 674-693.
[65] Laws, K.I.: Textured image segmentation, PhD thesis, University of Southern California, 1980.
[66] Peng, Y., Jiang, Y., Antic, T., Giger, M.L., Eggener, S., Oto, A.: A study of T2-weighted MR image texture features and diffusion-weighted MR image features for computer-aided diagnosis of prostate cancer, Proc. SPIE 8670, 86701H, 2013.
[67] Ginsburg, S.B., Rusu, M., Kurhanewicz, J., Madabhushi, A.: Computer extracted texture features on T2w MRI to predict biochemical recurrence following radiation therapy for prostate cancer, Proc. SPIE 9035, 903509, 2014.
[68] Vapnik, V.N.: The Nature of Statistical Learning Theory, Second Edition, Springer, NY, 2000.
[69] Freund, Y., Shapire, R.: A decision-theoretic generalization of online learning and an application to boosting, J. Comput. Syst. Sci. 55(1), 1997, pp. 119-139.
[70] Clausi, D.A., Jernigan, M.E.: Designing Gabor filters for optimal texture separability, Pattern Recognition 33(11), 2000, pp. 1835-1849.
[71] Duda, R., Hart P., Stork D.: Pattern Recognition, Second Edition, John Willey and Sons, 2001.
[72] Fukunaga, K.: Introduction to Statistical Pattern recognition, Second edition, Academin Press, San Diego, CA, USA, 1990.
[73] Hanley, J.A.: Receiver operating characteristic (ROC) methodology: the state of the art, Crit. Rev. Diagn. Imaging 29(3), 1989, pp. 307-335.
[74] Hosmer, D.W., Lemeshow, S., Sturdivant R.X.: Applied Logistic Regression, Third Edition, John Wiley & Sons, Inc., Hoboken, NJ, US, 2013.
[75] Bishop, C.M.: Neural Networks for Pattern Recognition, Oxford University Press, NY, USA, 1995.
[76] Ripley, B.D.: Pattern Recognition and Neural Networks, Cambridge University Press, Cambridge, UK, 1996.
[77] Costa, L. da F., Cesar, R.M.: Shape Analysis and Classification: Theory and Practice, CRC Press, Inc., Baca Raton, FL, USA, 2000.
[78] Turner, M.R.: Texture discrimination by Gabor functions, Biol. Cybern. 55(2-3), 1986, pp. 71-82.
[79] Sun, C., Wee, W.G.: Neighboring gray level dependence matrix for texture classification, Comput. Vision, Graph. Imag. Process. 23(3), 1983, pp. 341-352.
[80] Amadasun, M., King, R.: Textural features corresponding to textural properties, IEEE Trans. Syst. Man Cybern. 19(5), 1989, pp. 1264-1274.

[81] Specht, D.F.: Probabilistic Neural Networks, Neural Networks 3(1), 1990, pp. 109-118.

[82] Pearson, K.: On lines and planes of closest fit to systems of points in space, Phil. Mag. 2(6), 1901, pp. 559-572.

[83] Sachdeva, J., Kumar, V., Gupta, I., Khandelwal, N., Ahuja, C.K.: A novel content-based active contour model for brain tumor segmentation, Magn. Reson. Imaging 30(5), 2012, pp. 694-715.

[84] Ojala, T., Pietikainen, M., Maenpaa, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, IEEE Trans. Pattern Anal. Mach. Intell. 24(7), 2002, pp. 971-987.

[85] Idrissa, M., Acheroy , M.: Texture classification using Gabor filters, Pattern Recognition Letters 23(9), 2002, pp. 1095-1102.

[86] Zhang, J., Tan, T., Ma, L.: Invariant texture segmentation via circular Gabor filters, Proc: 16th Int. Conf. Pattern Recognition vol. 2, 2002, pp. 901-904.

[87] Tiwari, P., Prasanna, P., Rogers, L., Wolansky, L., Badve C., Sloan, A., Cohen, M., Madabhushi, A.: Texture descriptors to distinguish radiation necrosis from recurrent brain tumors on multi-parametric MRI, Proc, SPIE, 9035, 90352B, 2014.

[88] Burt, P.J., Adelson, E.H.: The Laplacian pyramid as a compact image Code, IEEE Trans. Commun. 31(4), 1983, pp. 532-540.

[89] Dalal N., Triggs, B.: Histograms of oriented gradients for human detection, IEEE Computer Society Conf. Comput. Vision and Pattern Recognition, CVPR2005 vol. 1, 2005, pp. 886-893.

[90] Random Forests, Machine Learning 45(1), 2001, pp. 5-32.

[91] Yang, C., Chuang, L., Yang, C.: IG-GA: a hybrid filter/wrapper method for feature selection of microarray data, J. Med. Biol. Eng. 30(1), 2010, pp. 23-28.

[92] Chan, T.F., Vese, L.A.: Active contours without edges, IEEE Trans. Image Process. 10(2), 2001, pp. 266-277.

[93] Kononenko, I.: Estimating attributes: analysis and extensions of relief, In Bergadano, F., de Raedt, L. (Ed): Lect. Notes Comput. Sc. 784, Springer-Verlag Berlin Heidelberg, 1994, pp. 171-182.

Dorota Duda

ANALIZA TEKSTUR JAKO NARZĘDZIE WSPOMAGANIA DECYZJI MEDYCZNYCH. CZĘŚĆ 1: NAJNOWSZE ZASTOSOWANIA DO WCZESNEGO WYKRYWANIA NOWOTWORÓW

Streszczenie: W ciągu ostatnich dwudziestu lat zaproponowano wiele komputerowych systemów wspomagania decyzji medycznych, opierających się na danych obrazowych. Systemy te są w stanie zlokalizować patologicznie zmienione obszary, opisać właściwości rozpatrywanych tkanek, jak również dokonać ich klasyfikacji. Istotnym źródłem informacji zawartej w obrazie jest jego tekstura. Cyfrowa analiza tekstur pozwala wykryć znacznie więcej szczegółów obrazu, niż zwykła analiza wizualna. Odpowiedni dobór metod analizy tekstur może przyczynić się do znacznego podwyższenia liczby trafnie rozpoznanych schorzeń. Wybór ten często zależy od niuansów danego problemu diagnostycznego.
Niniejsza praca stanowi przegląd najczęściej stosowanych metod analizy tekstur (statystycznych, opierających się na modelach, wykorzystujących filtry) oraz pokazuje ich zalety i ograniczenia. Zawiera również przegląd najnowszych systemów do wczesnego wykrywania i rozpoznawania nowotworów, opierających się na analizie tekstury.

Słowa kluczowe: obrazowanie medyczne, analiza obrazów, tekstura, selekcja cech, wspomaganie decyzji medycznych, diagnoza wspomagana komputerowo

Artykuł zrealizowano w ramach pracy statutowej S/WI/2/2013.